

Disentangling variational bias: the roles of development, mutation and selection

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1 **Abstract**

2 The extraordinary diversity and adaptive fit of organisms to their environment depends fundamen-
3 tally on the availability of variation. While many evolutionary studies assume that random mutations
4 produce isotropic phenotypic variation, the distribution of variation available to natural selection is
5 more restricted, as the distribution of phenotypic variation is affected by a range of factors in de-
6 velopmental systems. Here, we revisit the concept of developmental bias – the observation that the
7 generation of phenotypic variation is biased due to the structure, character, composition, or dynamics
8 of the developmental system – and argue that a more rigorous investigation into the role of develop-
9 mental bias in the genotype-to-phenotype map will produce fundamental insights into evolutionary
10 processes, with potentially important consequences on the relation between micro- and macroevolu-
11 tion. We discuss the hierarchical relationships between different types of variational biases, including
12 mutation bias and developmental bias, and their roles in shaping the realized phenotypic space. Fur-
13 thermore, we highlight the challenges in studying variational bias and propose potential approaches
14 to probe developmental bias.

15 Introduction

16 The observed diversity of life on Earth represents a fraction of theoretically possible phenotypes in
17 living organisms (Lewontin, 1979; Alberch, 1989, 1980; McGhee, 2006). Indeed, the fossil records
18 demonstrate prolonged periods of stasis in numerous lineages, and convergent evolution is widespread
19 (Allen *et al.*, 2008; Alberch, 1985). Yet, an enduring fundamental assumption of modern evolution-
20 ary genetics is that “universal variability – small in amount but in every direction” is a key factor
21 governing the agency of natural selection (Wallace, 1871; Hine *et al.*, 2014). For example, Fisher’s
22 geometric model assumes that mutations are isotropic, i.e., the magnitude and direction of effects
23 prior to selection are random in phenotypic space (Fisher, 1999; Tenaillon, 2014). This assumption
24 remains a dominant paradigm in population genetics, despite mounting evidence challenging its uni-
25 versality (Wright, 1984; Wagner & Zhang, 2011). Phenotypic variation is profoundly structured, and
26 variation and evolution are related at multiple timescales (Melo *et al.*, 2016; Houle *et al.*, 2017; Hol-
27 stad *et al.*, 2024). While functional and population geneticists have made great progress towards an
28 understanding of heredity, mapping genotype onto phenotype, and the mechanisms and consequences
29 of natural selection, the structure of variation accessible to selection remains elusive (Arthur, 2010).
30 The structure of variability leads to variational constraints, defined by limitation and biases in the
31 variability of phenotypic characters, which is one of the central classes of evolutionary constraint
32 (Pigliucci & Preston, 2004). These constraints are the outcome of a broader set of factors, including
33 genetic architecture, mutation, development, and are observed at all levels of biological organization
34 (Fig. 1). Different types of constraints can affect evolutionary processes – and phenotypic outcomes
35 – in distinct ways. It is thus critical to clarify what we measure when we measure variational con-
36 straints, and how different types of variational bias relate to one another, as they are frequently
37 intertwined.

38 Identifying the sources of variational bias

39 Variational constraints are routinely characterized by measuring the linear association between traits
40 in a population, and covariance matrices derived from these phenotypic measurements will capture
41 different aspects related to the causes and consequences of variational bias (Arnold *et al.*, 2008; Step-
42 pan *et al.*, 2002; Henry & Stinchcombe, 2023; Houle *et al.*, 2017; Falconer *et al.*, 1996; Penna *et al.*,
43 2017; Melo *et al.*, 2019). For example, genetic information summarized by the additive genetic
44 variance-covariance matrix – commonly referred to as \mathbf{G} – is a common measure of variational con-
45 straint in plant and animal breeding. \mathbf{G} specifically describes trait covariance due to pleiotropic

alleles, wherein variation at a single locus has effects on multiple traits, or due to linkage disequilibrium of two loci that are strongly associated in populations (Lande, 1980; Lynch *et al.*, 1998; Falconer *et al.*, 1996; Conner *et al.*, 2004). In evolutionary quantitative genetics, \mathbf{G} represents an important constraint because it describes the degree to which the genetic architecture (i.e., how traits are genetically connected to each other) may determine the response of a population to selection (Schluter, 1996; Lande & Arnold, 1983). Indeed, the genetic variation or \mathbf{G} is the most relevant parameter to the concept of “evolvability”, viewed as the population’s capacity to respond to directional selection (Jones *et al.*, 2007; Hansen & Houle, 2008). The context-dependency of \mathbf{G} , the evolution of evolvability itself, and how evolvability predicts the trait divergence and stasis under selection has garnered much of the empirical and theoretical attention to variational bias over recent decades (Wood & Brodie III, 2015; Opedal *et al.*, 2023; Walter, 2023; Pujol *et al.*, 2018; Mallard *et al.*, 2023a,c; Le Rouzic *et al.*, 2013; Hansen & Wagner, 2023; Walsh & Blows, 2009; Walter & McGuigan, 2023; Arnold *et al.*, 2008; Chenoweth *et al.*, 2010; Johansson *et al.*, 2021; Voje *et al.*, 2023; Holstad *et al.*, 2024).

While \mathbf{G} is a measure of the amount and structure of standing genetic variation, new variation generated by new mutations can be characterized by a mutational variance–covariance matrix \mathbf{M} (Dugand *et al.*, 2021; Houle *et al.*, 2017). The \mathbf{M} -matrix can be estimated through mutation accumulation (MA) experiments under a relatively selective-neutral environment. While \mathbf{M} itself provides information about the Genotype-to-Phenotype map, and hence developmental bias, it also captures bias caused by heterogeneous mutation rates and mutation spectra across the genome (Fig. 1)(James *et al.*, 2023; Rohner & Berger, 2023; Sane *et al.*, 2023; Cano *et al.*, 2023; Yampolsky & Stoltzfus, 2001; Katju & Bergthorsson, 2019; Agashe *et al.*, 2023; Couce & Tenaillon, 2019). In other words, \mathbf{M} can reflect the inherent limitations in the genotype space that favor specific mutational outcomes (e.g., more mutable single nucleotide, transition-transversion bias). Thus, \mathbf{M} acquired through mutation accumulation experiment includes developmental bias, but not limited to developmental bias (Rohner & Berger, 2023). Mutation bias is the bias specifically produced during the mutational process (Fig. 2 Right) without including the effects of development and selection on phenotypes (Fig. 2 Middle). Thus, \mathbf{M} , the mutation variance-covariance matrix, naturally captures both developmental and mutation bias.

The magnitude and direction of \mathbf{G} can provide information about the degree to which evolutionary constraints may be present in a population. \mathbf{G} is the product of many factors, including development, mutation, selection, drift, migration, and inbreeding. (Guillaume & Whitlock, 2007; Chebib

78 & Guillaume, 2017; Chantepie & Chevin, 2020; Phillips *et al.*, 2001; Cai *et al.*, 2023) The specific
79 mechanisms and relative contributions of various factors in shaping and maintaining \mathbf{G} remain poorly
80 understood. A major complication is that, almost certainly, these contributions can drastically dif-
81 fer between different suite of traits or trait combinations. Empirically, the contributions of \mathbf{M} and
82 selection to shaping \mathbf{G} can be inferred by comparing \mathbf{G} to \mathbf{M} , or comparing \mathbf{G} to γ , the matrix
83 describing multivariate nonlinear selection. If \mathbf{G} is shaped by \mathbf{M} , then, in equilibrium, \mathbf{G} should be
84 proportional to \mathbf{M} (Cheverud, 1984). A recent simultaneous estimate of both \mathbf{G} and \mathbf{M} in the same
85 *Drosophila serrata* population indeed shows some proportionality between the two matrices, showing
86 a contribution of mutation bias to additive genetic variation (Dugand *et al.*, 2021). Surprisingly, in
87 this population, \mathbf{M} appears to be more constrained than \mathbf{G} , which implies that selection can act to
88 break constraints imposed by mutation, instead of the usual picture of stabilizing selection increas-
89 ing genetic correlations. This result illustrates how nonintuitive and case dependent the shaping
90 of \mathbf{G} might be. Furthermore, other multivariate analyses suggest differences between \mathbf{G} and \mathbf{M}
91 (Latimer *et al.*, 2011; Houle *et al.*, 1994; Keightley *et al.*, 2000; Latimer *et al.*, 2014; Camara *et al.*,
92 2000; Mallard *et al.*, 2023b). Notably, Houle *et al.* 2017 found \mathbf{G} and \mathbf{M} to be markedly similar for
93 wing traits in *Drosophila melanogaster*. Moreover, \mathbf{M} reliably predicts patterns of wing divergence
94 across drosophilids (Houle *et al.*, 2017), suggesting a major role for mutation in determining long-term
95 evolutionary divergence, as well as \mathbf{G} .

96 One distinction between \mathbf{G} and other variational constraint is that developmental and mutational
97 biases can vary among individuals and genotypes both empirically and in theory, (Psujek & Beer,
98 2008; Uller *et al.*, 2018; Braendle *et al.*, 2010; Mallard *et al.*, 2023b; Conradsen *et al.*, 2022) while
99 \mathbf{G} , or more broadly phenotypic correlation, is a measure of a given population. The (co)-variance in
100 \mathbf{G} explained by each polymorphic locus is affected by allele frequencies and the magnitude of allelic
101 effects in an individual (Benfey & Mitchell-Olds, 2008; Kelly, 2009).

102 Theoretical and empirical studies suggest that \mathbf{M} -induced genetic correlations tend to be more sta-
103 ble than genetic correlation caused by selection, implying that identifying the mechanisms causing
104 genetic correlation may help us understand the evolution of \mathbf{G} (Jones *et al.*, 2003; Cai *et al.*, 2023).
105 Furthermore, the genetic architecture of \mathbf{G} may be informative in inferring the drivers of \mathbf{G} (se-
106 lection versus \mathbf{M}) since those structures of linkage disequilibrium and pleiotropy in the genome are
107 footprints of distinct forces when inducing and maintaining \mathbf{G} . Selection can also reshape \mathbf{M} (Fig.
108 2), although the timescale on which the evolution of \mathbf{M} occurs – relative to phenotypic evolution –
109 is unclear; we may be able to treat \mathbf{M} as constant under most evolutionary scenarios (Mallard *et al.*,

110 2023b; Conradsen *et al.*, 2022).

111 Collectively, we argue that clear and distinctive definitions of variational biases at different levels are
112 needed to ensure effective communications and nuanced analyses in the future (Fig. 1).

113 **Developmental bias in the production of phenotype**

114 An important aspect of genotype-to-phenotype maps is that they are highly non-linear and structured
115 in nature. Therefore, random mutations do not necessarily produce random phenotypic changes. The
116 distribution of phenotypic variants that occur as a result of genetic and environmental variation is
117 channelled by the developmental processes that transform the embryonic phenotype into the adult
118 form (Klingenberg, 2008; Snell-Rood & Ehlman, 2023). This developmental process imposes a bias
119 on the generation of phenotypic variation, arising from the structure, character, composition, or
120 dynamics of development, relative to the assumption of isotropic variation, resulting in developmental
121 bias (Maynard Smith *et al.*, 1985; Sears, 2014; Uller *et al.*, 2018; Alberch, 1989).

122 A number of empirical studies have hypothesized that an organism’s developmental system shapes the
123 trait-trait (co)variance observed in \mathbf{G} , which has been described as phenotypic integration (Pigliucci
124 & Preston, 2004). Development is therefore a critical factor in shaping the variational bias reflected
125 in \mathbf{M} and \mathbf{G} (Hallgrímsson *et al.*, 2009). Substantial evidence has shown that this developmental
126 bias is common (Staps *et al.*, 2023; Machado *et al.*, 2023; Couzens *et al.*, 2021; Rohner & Berger,
127 2023; Staps *et al.*, 2023). For example, the developmental regulation of tetrapod limb generates
128 bias in the number and distribution of digits and limbs (Alberch & Gale, 1985; Wake, 1991); In-
129 teractions among components in a developmental system bias trait-trait relationships in insects and
130 pigment coloration of insect wings (Brakefield & Roskam, 2006; Prud’homme *et al.*, 2006). While
131 selection ultimately shapes developmental systems, such intrinsic biases from developmental systems
132 are likely to be an important component of phenotypic evolution (Wagner & Altenberg, 1996; Sears,
133 2014; Uller *et al.*, 2018; Moczek *et al.*, 2015; Staps *et al.*, 2023). Firstly, the bias in genotype and
134 phenotype production stands as a distinct phenomenon from phenotypic adaptation, each subject to
135 separate evolutionary dynamics (Wagner & Altenberg, 1996; Watson *et al.*, 2014). Conventionally,
136 developmental biases are believed to undergo more gradual evolution in comparison to the traits
137 that they influence (Watson *et al.*, 2014). Secondly, although certain parts of developmental systems
138 remain evolvable and susceptible to selective pressures, prevailing global constraints resist alteration
139 (Maynard Smith *et al.*, 1985; Brakefield, 2006). Exemplifying this notion, resource acquisition is
140 limited due to chemical, thermodynamic, and mechanistic constraints (Novak *et al.*, 2006; Lipson,

141 2015; Reding-Roman *et al.*, 2017), leading to trade-offs between, e.g., growth rate and yield in *E.coli*
142 (Novak *et al.*, 2006), or between spore number and quality in *D. discoideum* (Wolf *et al.*, 2015). An-
143 other famous example comes from the metabolic scaling law, which states that metabolic rate scales
144 with body mass to the power of 3/4. A wide range of organisms over several orders of magnitude
145 in body mass conform to this law. Of course, one could argue that it is purely natural selection
146 that forces these points to fall along a predictable trajectory across evolutionary history. But there
147 are theoretical arguments that demonstrate such metabolic scaling is caused, at least in part, by
148 physical forces imposing constraints, or by biases in patterns of energy allocation (White *et al.*, 2022;
149 Kooijman, 2010; West *et al.*, 2001).

150 Importantly, the relationship between adaptation of traits and developmental bias is not simply one of
151 opposition, but is instead the result of a continuous dynamic interaction. Therefore, we can only ask
152 whether developmental bias alters evolutionary trajectories in relatively short timescales (Pigliucci &
153 Preston, 2004). For instance, two regulatory networks may yield similar functional outputs but differ
154 in their variational properties, leading to different evolutionary biases (Schaerli *et al.*, 2018). However,
155 over a timescale of macroevolution, it is difficult to disentangle the contribution of developmental
156 bias and selection in phenotypic adaptation. Because firstly, bias of phenotypic production can
157 evolve. Secondly, the evolutionary history of variational bias cannot be easily reconstructed unless
158 the mutation and developmental bias remain relatively constant over macroevolutionary timescales.
159 An outstanding practical problem is: can we treat developmental bias as constant, and at what
160 timescales (Fig. 2).

161 **Emerging methods for measuring developmental bias**

162 The evolutionary significance of developmental bias has long been controversial because, we argue, it
163 can be difficult to accurately diagnose. Natural selection and random genetic drift strongly affect the
164 patterns of phenotypic variation within and between populations, making it unsatisfying to rely solely
165 on measurement of existing phenotypic variation when attempting to identify developmental bias
166 (Lynch *et al.*, 1998; Roseman, 2020). Given that both developmental bias and selection could create
167 similar phenotypic distribution in natural populations, it is generally difficult to distinguish between
168 the two (Schluter, 1996; Pigliucci & Preston, 2004). To quantitatively investigate developmental
169 bias, researchers need to assess the propensity of phenotypic production prior to selection rather
170 than merely observing the current state of variation (Wagner & Altenberg, 1996).

171 One traditional approach to distinguish between the effects of developmental bias and selection is

172 through mutation accumulation (MA) lines to assess the spectrum of phenotypic variation generated
173 by *de novo* mutation in the absence of selection (Zalts & Yanai, 2017; Braendle *et al.*, 2010; Houle
174 *et al.*, 2017). However, as mentioned above, *de novo* mutation captures not only the propensity of the
175 developmental system to vary but also heterogeneity in mutational rates and spectra across genome,
176 which constrains the mutation in genotype space (Stoltzfus & McCandlish 2017; Rohner & Berger
177 2023; James *et al.* 2023; Agashe *et al.* 2023; Sane *et al.* 2023; Fig. 1, e.g., more mutable single nu-
178 cleotide, transition-transversion bias, etc.) Alternatively, some well-studied developmental systems,
179 such as tooth morphology, can be modeled sufficiently well so that a large number of perturbations
180 can be simulated to evaluate the variability *in silico* (Salazar-Ciudad & Jernvall, 2010). However,
181 this method is only feasible for few systems for which we have a relatively complete knowledge of
182 intricate developmental dynamics.

183 Another approach to establish developmental bias is to measure symmetry of the left and right sides
184 of the same organism – so-called “fluctuating asymmetry” – (Rohner & Berger, 2023; Klingenberg &
185 McIntyre, 1998), which share both a genome and environment. However, the developmental process
186 may produce asymmetry in morphological traits due to inevitable consequences of molecular stochas-
187 ticity, which is often interpreted as developmental noise. A recent study showed that developmental
188 bias quantified using such internal variability in the dipteran wing predicts its evolution on both
189 short and long evolutionary timescales (Rohner & Berger, 2023). Ultimately, addressing the of evo-
190 lutionary role of developmental bias requires studies in more systems. We thus ask alternative and
191 existing ways to characterize developmental bias without being dependent on specific developmental
192 systems.

193 In line with the concept of fluctuating asymmetry, there are multiple ways to assess the propensity
194 of the system to vary by inducing mild and random (environmental or genetic) perturbations. The
195 phenotypic variation in a genetically identical population, under the same environmental condition,
196 has often been referred to as intra-genotypic variability (Metcalf & Ayroles, 2020; Bradshaw, 1965)
197 or phenotypic variability (Abley *et al.*, 2021; Ayroles *et al.*, 2015; Willmore *et al.*, 2007), which is
198 thought to be an emergent by-product of the developmental processes (Willmore *et al.*, 2007). Such
199 variability reflects both the results of stochasticity in molecular interactions and of external sources
200 caused by microenvironmental variation (Elowitz *et al.*, 2002; Sanchez & Golding, 2013; Cortijo *et al.*,
201 2019). These extrinsic and intrinsic small random fluctuations interact with developmental systems
202 and give rise to the phenotypic variability. Thus, we hypothesize that the variational properties
203 induced by random small perturbations most likely reflect the inherent attributes of the system

204 rather than a certain direction of perturbation (e.g., changes of a nutrient level, single gene knock-
205 out etc.). In fact, such phenotypic variability has been used to characterize developmental systems
206 in many studies (Kiskowski *et al.*, 2019; Klingenberg, 2019; Geiler-Samerotte *et al.*, 2020), though
207 these studies have not explicitly addressed developmental bias. For example, variational properties
208 under the same environmental condition across clonal cells help to quantify inherent relationships
209 among yeast morphology traits (Geiler-Samerotte *et al.*, 2020).

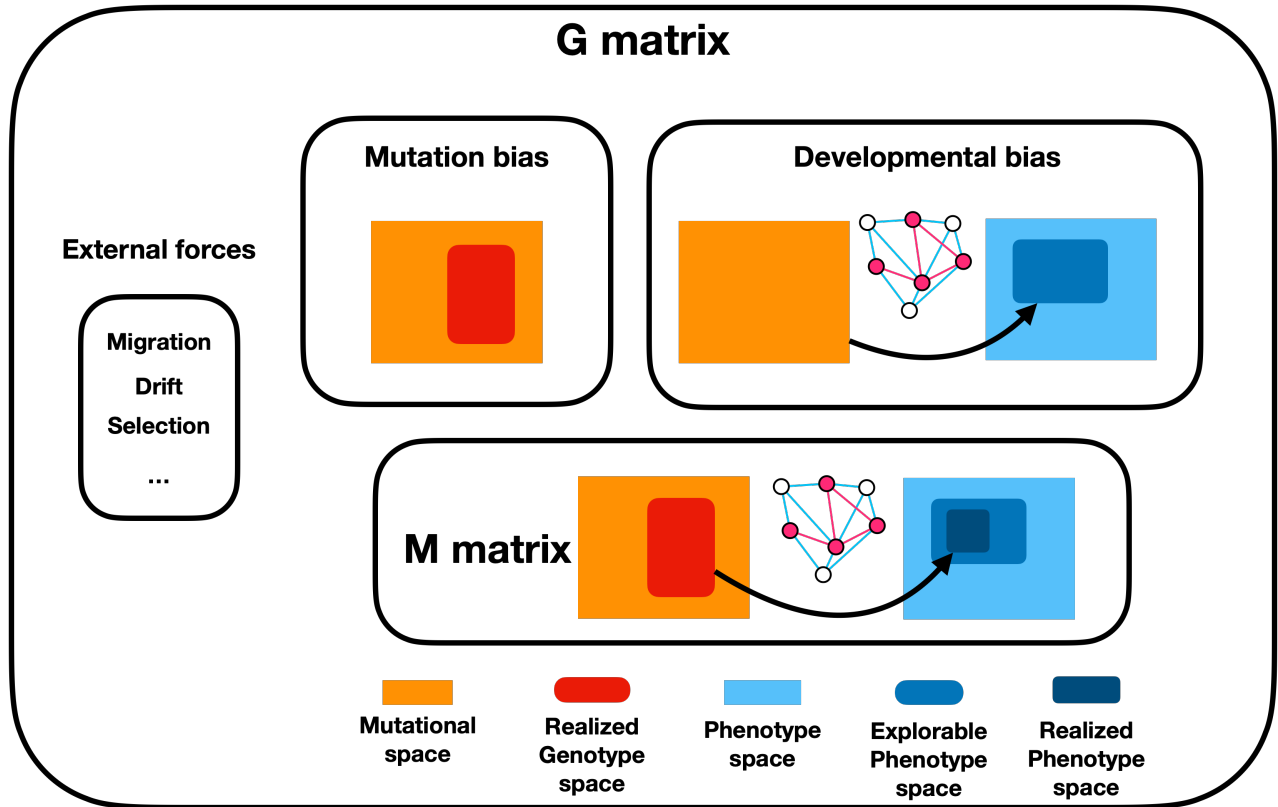
210 Over the last few decades, studies of gene expression evolution have proliferated owing to reduced
211 cost of RNA sequencing. A surge of studies in canalization, modularity, and phenotypic integration at
212 the molecular level has followed (Lea *et al.*, 2019; Cai & Des Marais, 2023; Melo *et al.*, 2023; Gibson,
213 2009). These concepts are all connected to the classic notion of developmental constraint (Melo *et al.*,
214 2016). Yet, few studies used expression variability to address these questions: much efforts in gene
215 expression variability have been taken to examine the genomic, epigenetic, and topological features
216 in determining the gene-specific expression variability level (Cortijo *et al.*, 2019; Barroso *et al.*, 2018).
217 We argue that genome-scale expression variability data can be exploited to investigate the bias in
218 the production of gene expression and, ultimately, contribute to our understandings of evolution in
219 gene expression (Wolf *et al.*, 2023).

220 Another way to impose random perturbations is through random mutation. As discussed above, the
221 variants captured in mutation accumulation experiments account for the heterogeneity of mutation
222 rates and other mutational bias across the genome (Fig. 1). Unfortunately, MA studies provide a very
223 limited view of the distribution of mutational effects because the number of spontaneous mutations
224 sampled in each study tends to be very low (Hodgins-Davis *et al.*, 2019). One approach to ameliorate
225 these limitations is to introduce mutation without incurring mutational bias during *de novo* muta-
226 tion. For example, genome-wide mutagenesis (Hodgins-Davis *et al.*, 2019) as opposed to *de novo*
227 mutation provides an empirical investigation of bias in the phenotypic production and reveal greater
228 neutral expression divergence than commonly used models of phenotypic evolution. Deep-sequencing
229 techniques can also be used to trace individual allele effects for single nucleotide variants across the
230 genome (Dolan *et al.*, 2021; Gitschlag *et al.*, 2023). A similar outcome and mutational landscape of
231 a given trait (trait combination) from wide-range variants across the genome would be indicative of
232 developmental or mutation bias. Alternatively, artificial recombinant populations provide mutational
233 perturbative materials for examining the propensity of the system to vary (Cai *et al.*, 2023; Fraser,
234 2020). In addition, systematic perturbation studies using the CRISPR-Cas9 methodology with the
235 scale of massive high-throughput phenotyping or RNA-sequencing (e.g., perturb-seq (Dixit *et al.*,

236 2016)) can be leveraged to examine the variational properties of organisms.

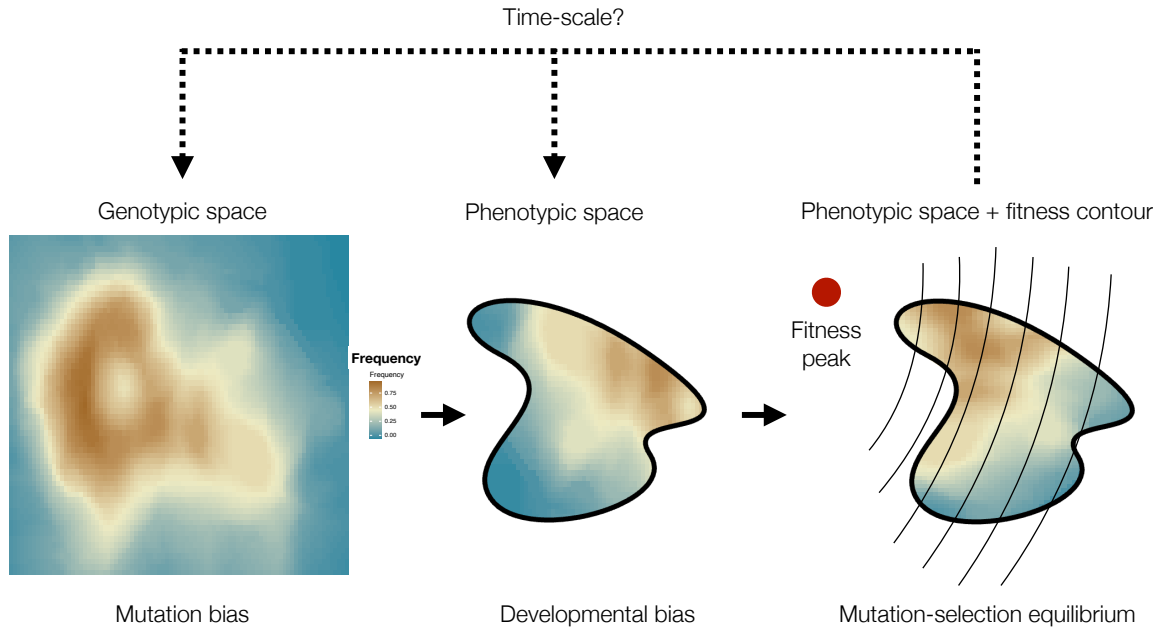
237 **Concluding remarks**

238 One long-standing suggestion for bridging the gap between micro- and macroevolution has been
239 through the study of evolutionary developmental biology and ontogeny (Machado *et al.*, 2023; Rolland
240 *et al.*, 2023). Here, we argue that progress in integrating micro- and macro-evolutionary theory
241 has been hampered by the common assumption in population genetics that genotype-to-phenotype
242 mapping is a straightforward exercise emerging from an invariant distribution of mutational effects.
243 There is substantial evidence that variational bias is common. Such bias may be caused by factors in
244 mutation, genetics, and development. We argue that clear and distinctive definitions of variational
245 biases at such different levels (Fig. 1 and Fig. 2) are needed to help better understand the role of
246 variational bias in adaptation and how evolution shapes variational bias. Furthermore, as we have
247 shown, developmental bias is notoriously difficult to establish empirically. We thus review and suggest
248 approaches aimed at identifying developmental bias and testing for its role in shaping phenotypic
249 evolution. In particular, we argue that a large number of untargeted and random perturbations
250 can be exploited to assess the propensity of the system to vary, and hence, the bias of phenotypic
251 production. Collectively, we present challenges in studying variational bias and its role in shaping
252 evolutionary history and impacting future adaptation.



253

254 **Figure 1: Hierarchical relationships of the concepts and empirical measurements related**
 255 **to variational biases.** Because of mutational bias, only a subset of random mutation is realized in
 256 the genotype space of possible mutations. The genotype space is translated to the phenotype space
 257 through the process of development, which can impose developmental bias. Not all phenotypes in the
 258 phenotype space are accessible due to developmental bias, which leads to an explorable phenotype
 259 space that is a subset of the total possible phenotype space. Mutation accumulation (MA) lines
 260 captures both the mutation bias and developmental bias, which leads to a realized phenotypic space
 261 that is a subset of (explorable) phenotypic space. Therefore, the “explorable” phenotypic space is
 262 influenced solely by developmental bias while the “realized” phenotypic space is a result of both
 263 mutation and developmental bias as captured by mutation accumulation (MA) lines. Other evolu-
 264 tionary forces such as selection, migration, and drift interact with mutational variation (**M**) in the
 265 realized phenotype space to shape **G**.



267

268 **Figure 2: A hypothetical scenario showing influences of mutation bias and developmental**
 269 **bias on adaptation.** Mutations are biased such that some mutations are more likely to occur than
 270 others (left). Developmental processes then translate genotypic variation into phenotypic space,
 271 potentially imposing developmental bias (middle). Such biased phenotypic distribution interacts
 272 with drift and selection to form the distribution of population under mutation-selection equilibrium
 273 (right). However, both mutation bias and developmental bias can evolve in response to selection.
 274 Whether the timescale of the evolution of developmental and mutation bias is longer than the trait
 275 adaptation is often unknown. Solid arrows represent processes occurring over short time scales
 276 (micro-evolution), while dashed arrows indicate processes that possibly occur over similar or longer
 277 evolutionary time scales (macro-evolution).

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